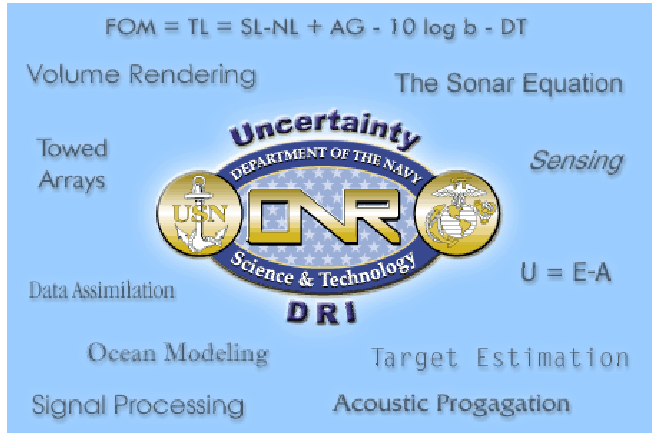


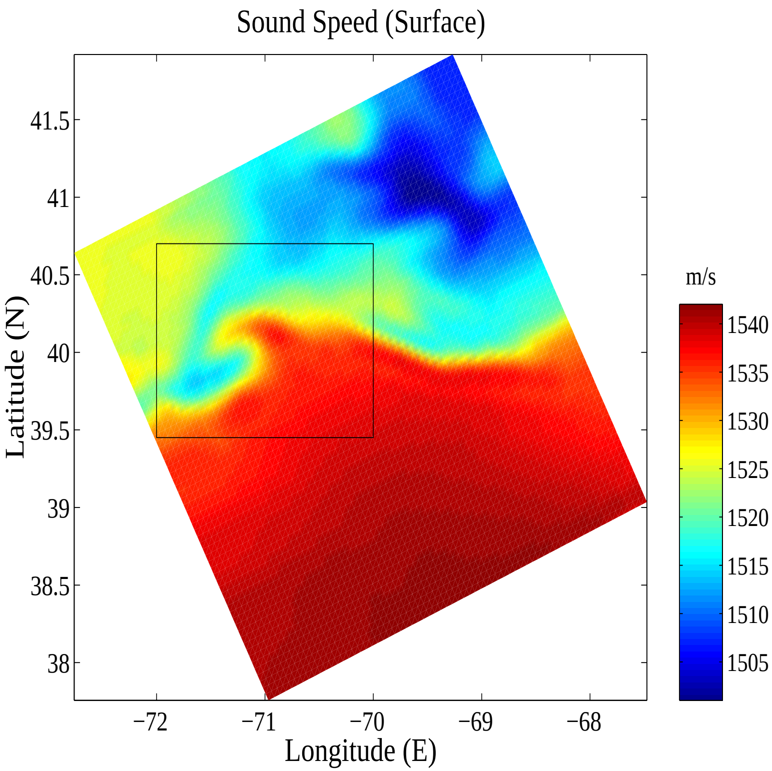
Modeling and Analyzing the Propagation of Uncertainty from Environmental through Sonar Performance Prediction

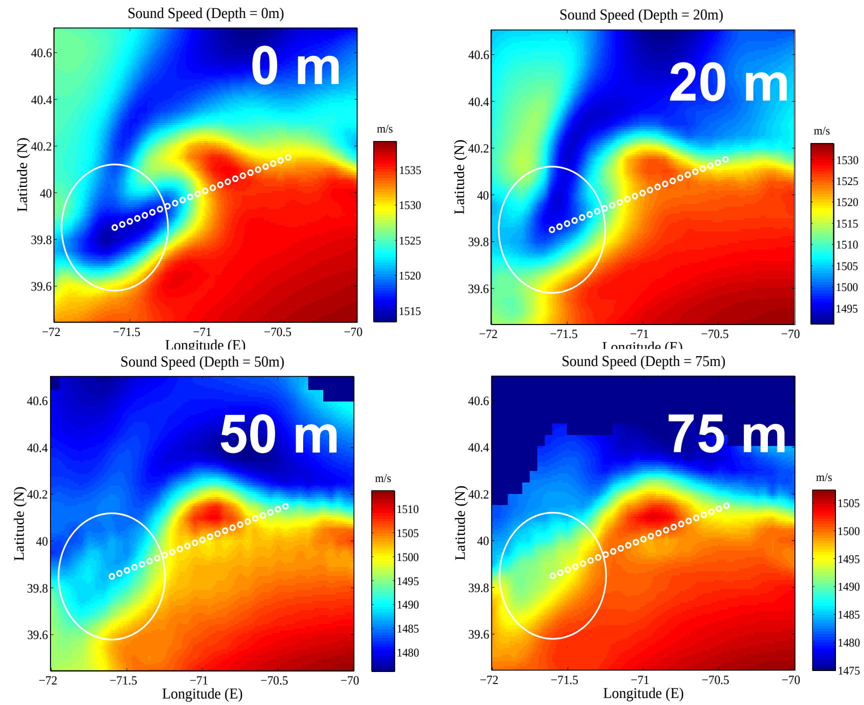
Bruce Cornuelle, Harry Cox, Peter Gerstoft, Kevin Heaney, Heaney, Bill Hodgkiss, Paul Hursky, Jeff Krolik, Bill Kuperman*,

Loren Nolte, Mike Porter

***coordinator**

AREA WIDE OCEANOGRAPHY





Courtesy: WHOI/Harvard

Outline

- Review & Overview -- *Bill Kuperman*
- Oceanography -- *Bruce Cornuelle*
- Acoustics & Area Wide Prediction -- *Mike Porter*
- Probability and Statistics of Acoustical Signal Processing -- *Loren Nolte*

Overview

- **Sonar Equation summarizes components of performance prediction**
- **Oceanography drives the acoustics**
- **Acoustics Drives System Performance**
- **"Operator" views System Performance Prediction as (un)reliable guide.**
- **Operator USES System Performance Prediction to aid in Tactical Decisions (TDA). [e.g.. Expert System]**
- ***Goal of our program: <u>Develop a methodology to assign a certainty or reliability measure to Performance Prediction which encompasses the uncertainties along the whole Oceanography -->System Model path</u>***

System Level Overview

Acoustic Predictions are characteristically high precision and low accuracy

Uncertainty – primarily inputs

Bathymetry/geoacoustics in shallow water

Sound Speed vs. range

Frequency dependence?

Variability – temporal and spatial

Range dependence

Effects of motion

Sensitivity – how does the answer depend on the parameters?

Example:

- *For flat TL vs. range environments: a few dB = lots of range uncertainty*
- *For steep TL vs. range environments: a few dB = little range uncertainty*

System Level Overview

Acoustic performance is a story, not a number. How do we tell the story?

To build credibility we must communicate :

- Confidence bounds
- Sensitivities
- Critical local parameters (SVP? Bathymetry? Bottom?)

Potential Uses:	Requirements:
Range Prediction	**Primarily TL** **Sensitivity, Confidence, f-dep.**
Tactics: **-detection** **-counter-detection**	**Sensitivity to adjustable parameters:** **- Depth** **- Speed** **- Location**
Ranging	**More precise acoustic prediction depending on algorithm.**

Sonar Processing

Passive Acoustics:

How sensitive is TL to environmental parameters

Noise field sensitive to propagation (measurable)

Sensitive to non-environmental parameters:

- Target Depth
- Target aspect
- Radiated noise

Active Acoustics:

Two way TL makes propagation more important

Bottom reverb – dominant interference:

- Poor databases and measurement approaches
- Poor physical understanding
- Frequency dependence?

Target strength depends strongly on aspect

Example: Minimum Detection Level

Sonar Equation

$$SE = SL - TL - RD - NL + AG$$

SE : Signal excess in dB

SL : Source level of target in dB//1uPa^2

TL : Transmission loss in dB (modeled as a variable in range)

RD : Recognition differential in dB (S/N at detection threshold)

NL : Ambient noise in dB//1uPa^2 /Hz

AG : Array gain in dB

Minimum Detection Level (MDL)

$$MDL(r, \theta) = TL + RD - AG + NF$$

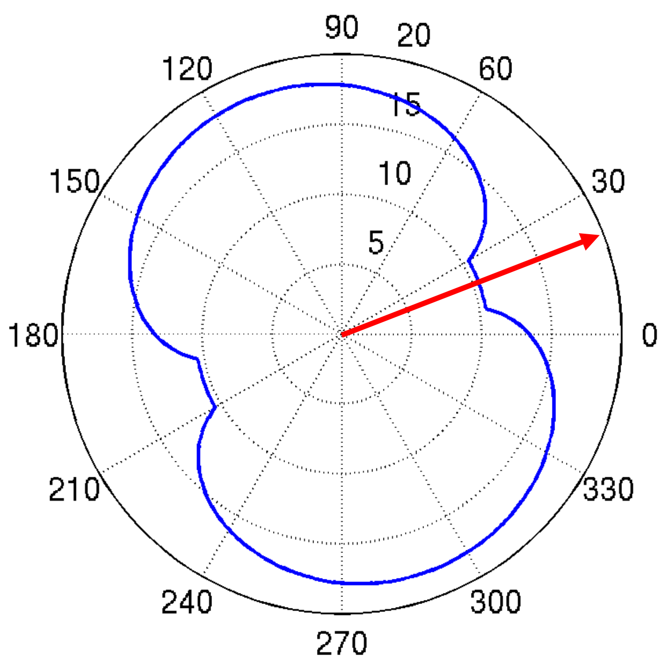
$$\left\{ \begin{array}{l} NF = 10*\log \{180*[N_B(\theta+\phi)+N_B(\theta-\phi)]/\sin\phi\} \\ N_B = 10^{NL/10}, \text{NL} \sim 77 \text{ dB (omni noise level)} \\ RD = 0 \text{ dB}, \\ AG = 18 \text{ dB}, \\ \phi\text{: ship heading} \end{array} \right.$$

***MDL: A target located at the position whose source level is equal to or greater than MDL(r) has greater than a 50% probability of being detected (with a specified false alarm rate)**

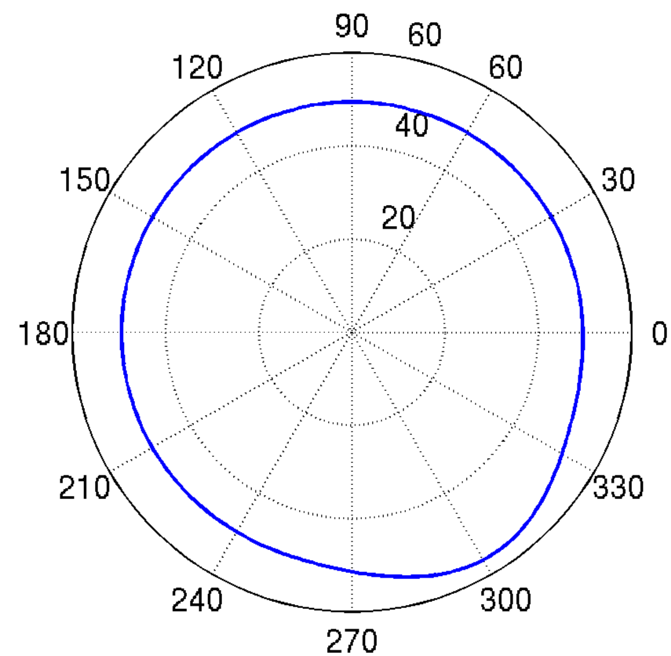
Kuperman et al, June 2001

Array Gain & Ambient Noise

Array Gain (dB)



Ambient Noise (dB/1 deg)



Omni noise level = 77 dB

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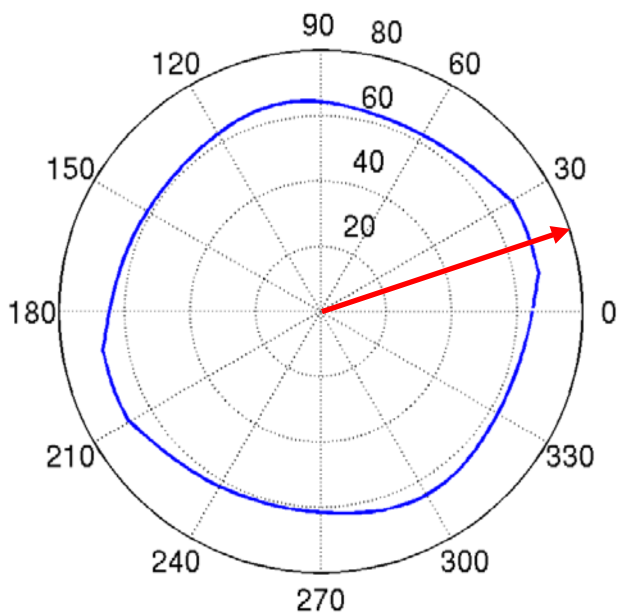
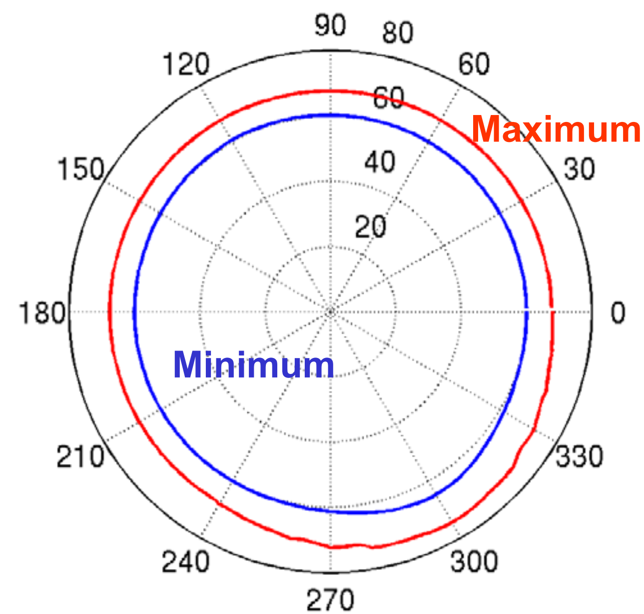
Array Gain & Ambient Noise

Ship Heading (20°)



Min/Max

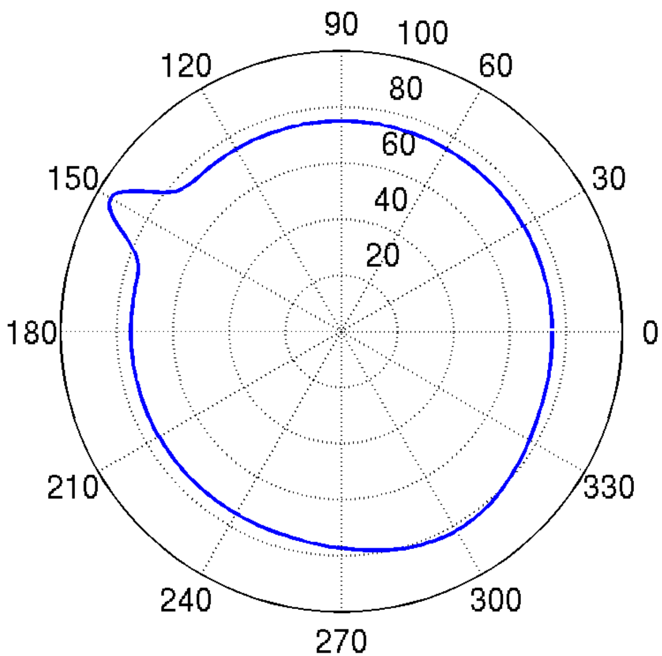


$$\mathbf{NF\text{-}AG = 10{*}\log \{180{*}[N_B(\theta+\phi)+N_B(\theta-\phi)]/\sin\phi\} - AG}$$

Kuperman et al, June 2001

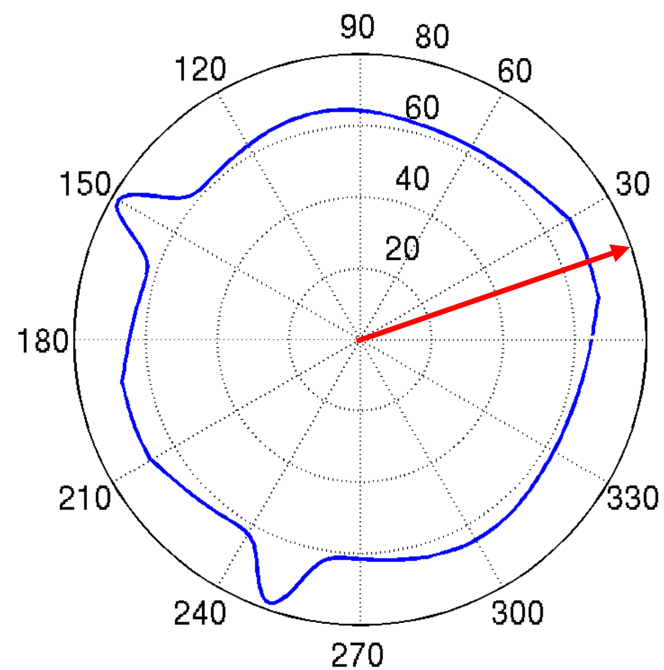
Discrete Ship Noise

Ambient Noise (dB/1 deg)



Omni noise level = 80 dB

NL - AG (dB)



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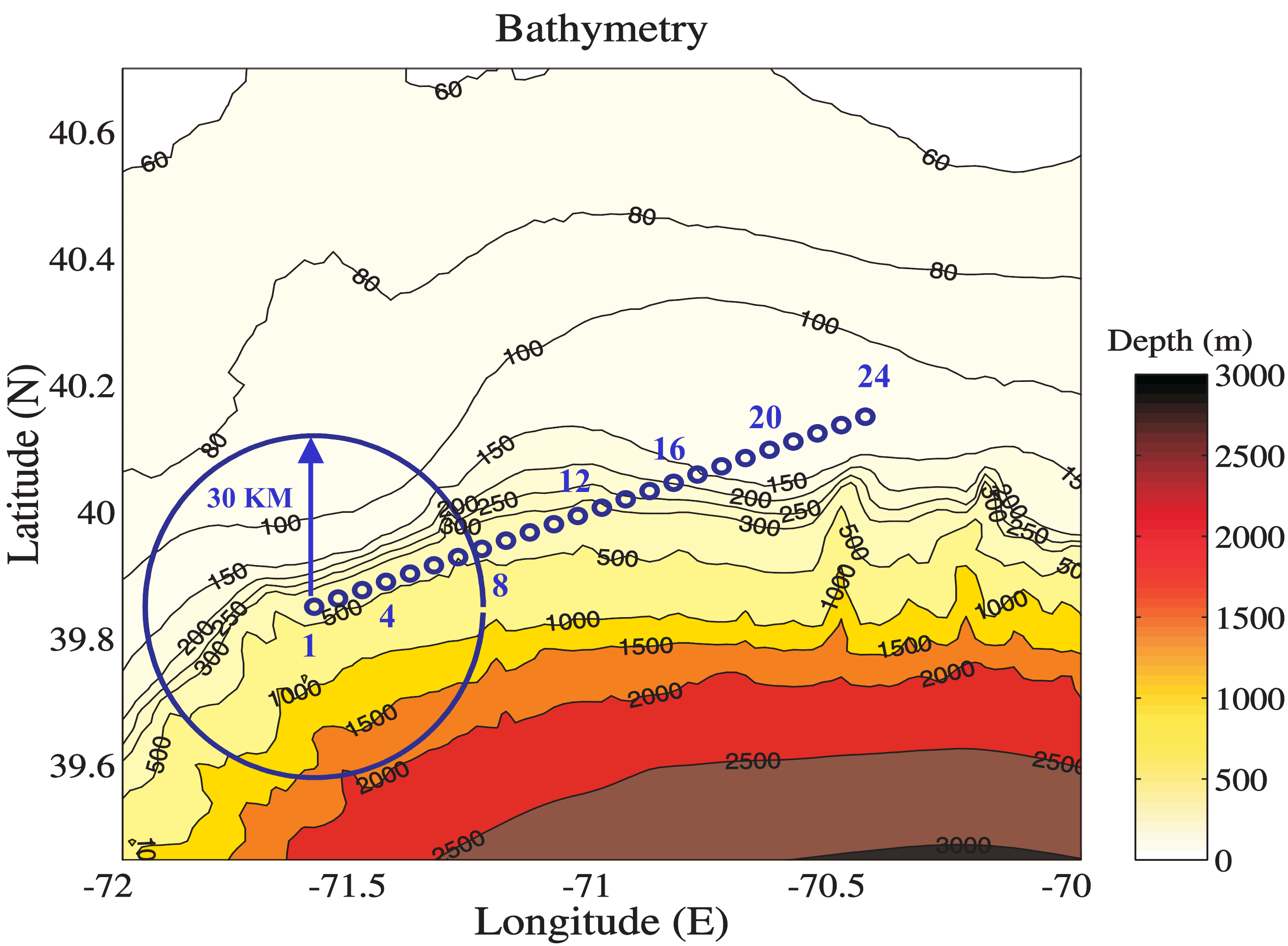
MDL along the Track

- Distant Shipping Traffics
- Discrete/Distant Shipping Traffics

Bathymetry



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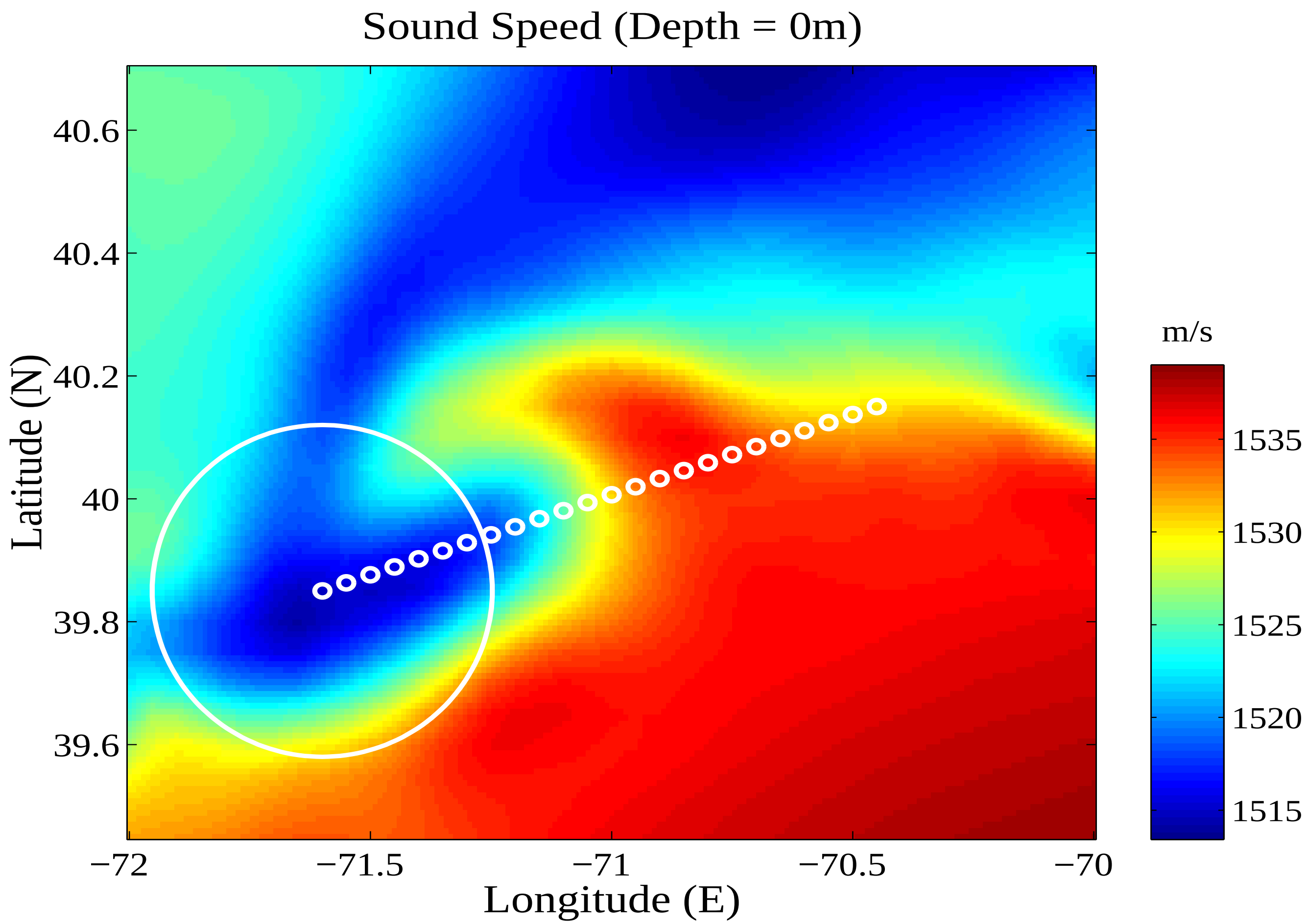
Surface Sound Speed



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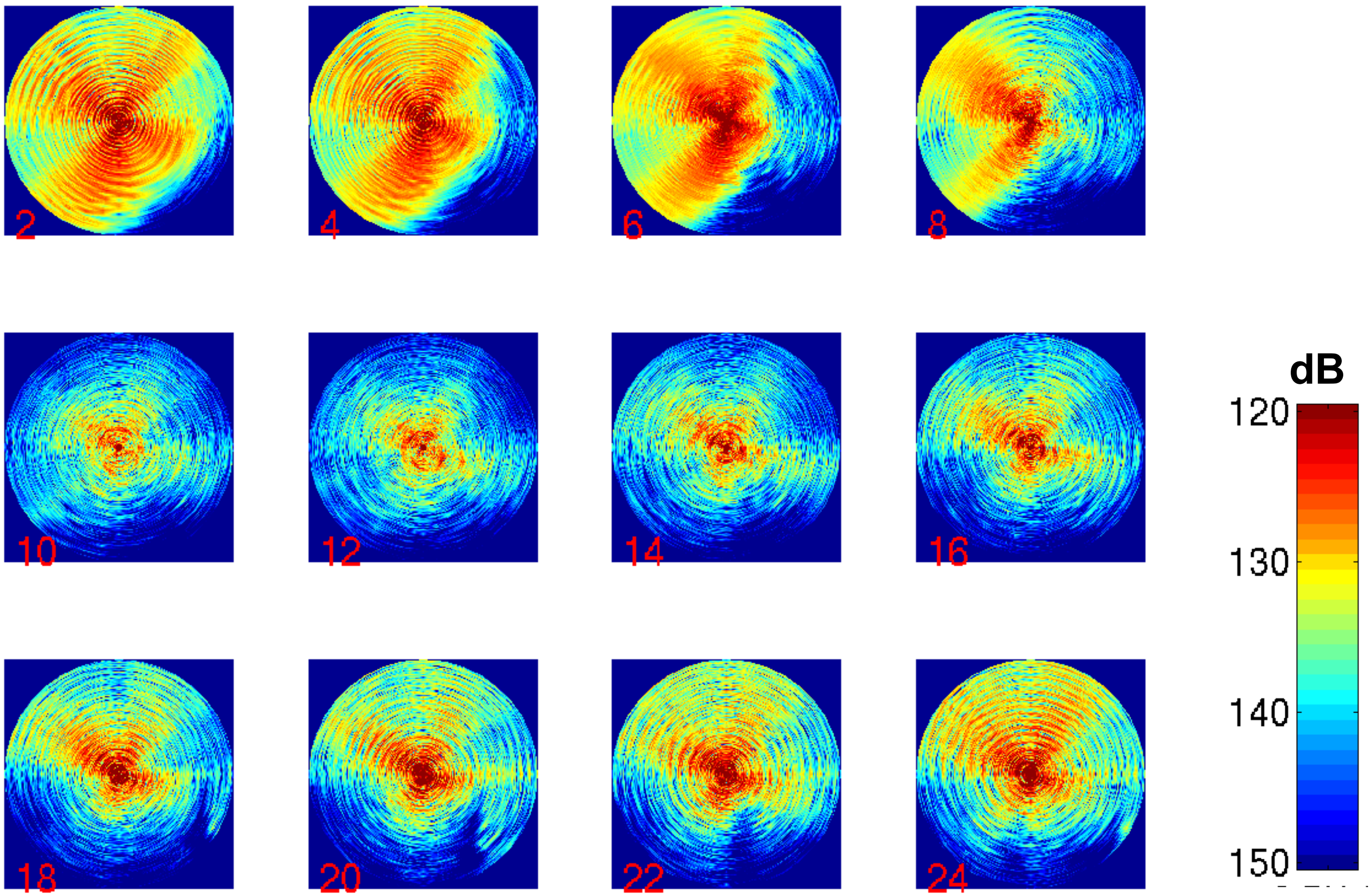
MDL (Real Ocean)



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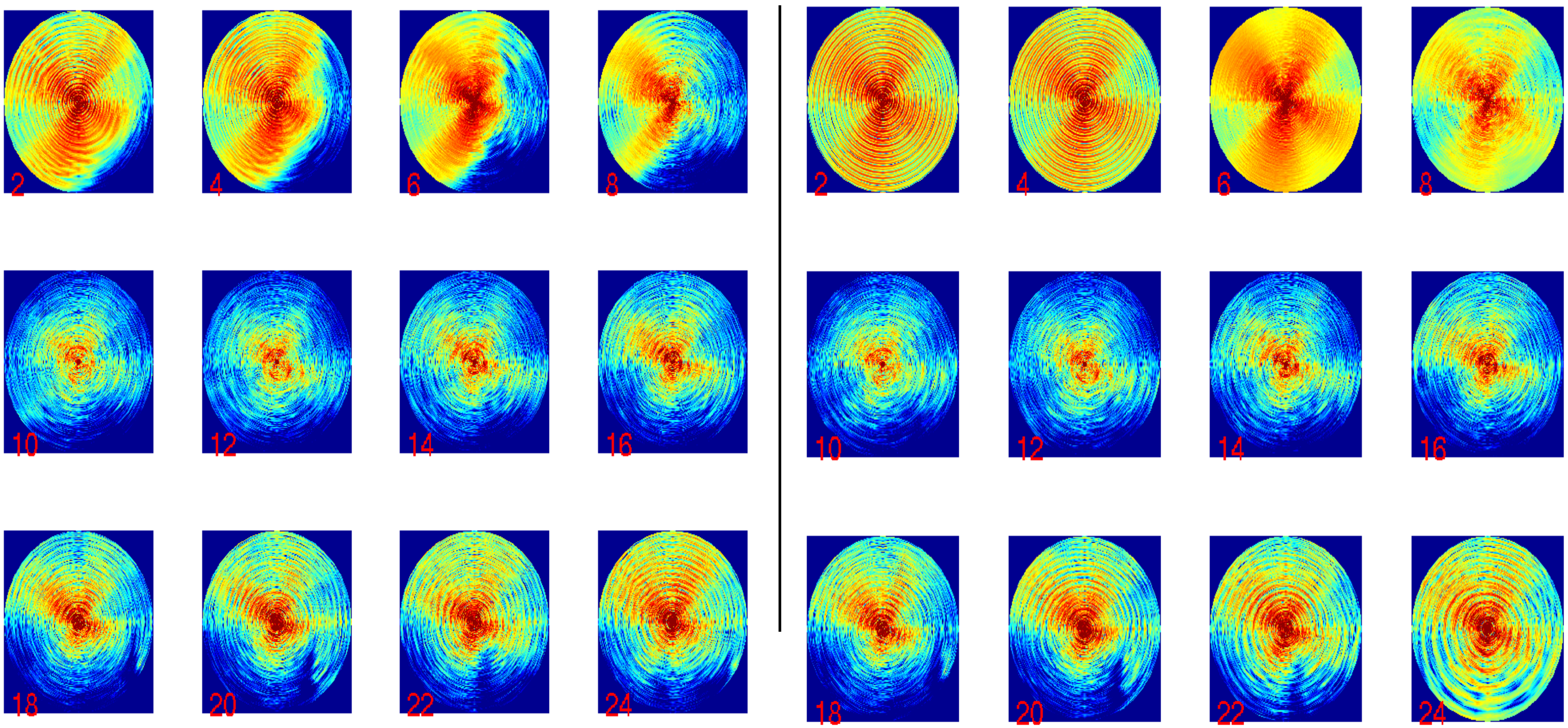
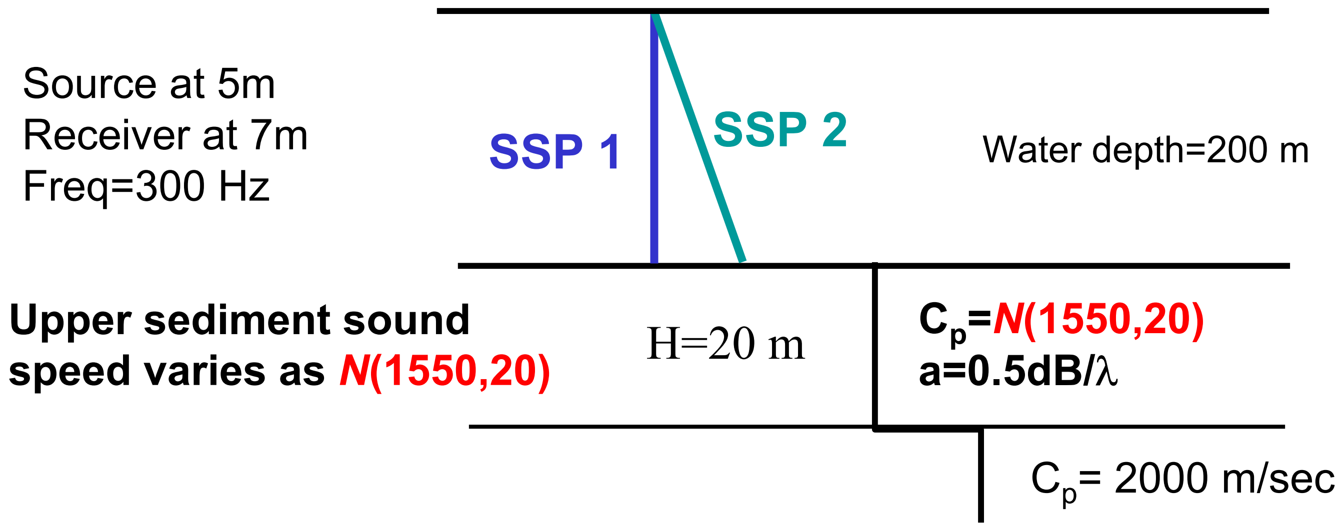
Real and Single Profile Performance Prediction



Impact of geoacoustics

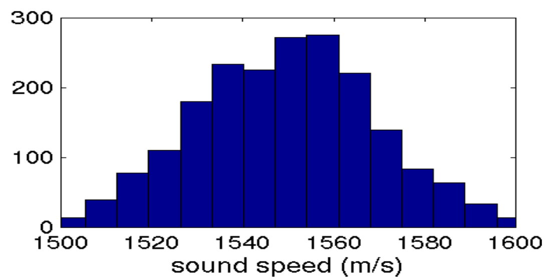
- Geoacoustic variability can be an important factor in performance prediction, depending on how much bottom interaction we have in a given environment.
- Will compare how geoacoustic variability impacts incoherent TL for two water column SSPs:
  - Isovelocity profile (**SSP 1**)
  - Upward refracting profile (δc=20 m/s) (**SSP 2**)

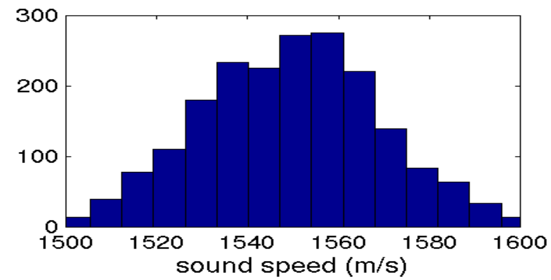


How geoacoustic uncertainty impacts TL uncertainty in two different SSPs

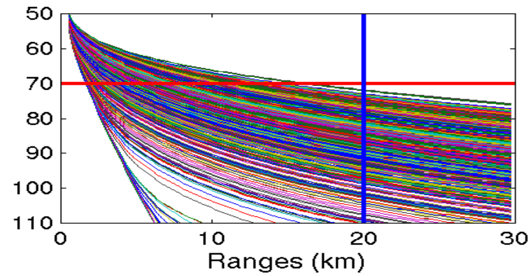
Isovelocity SSP | **Upward refracting SSP**

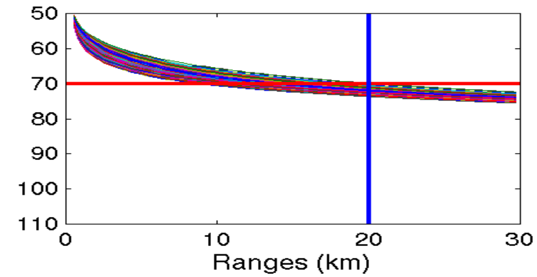
Sediment sound speed distribution (2000 realizations)



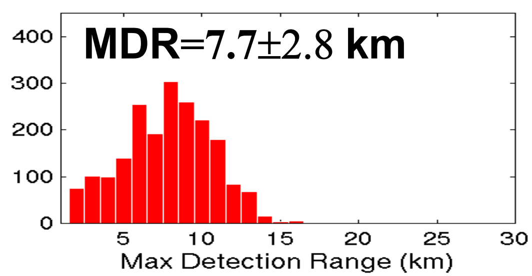


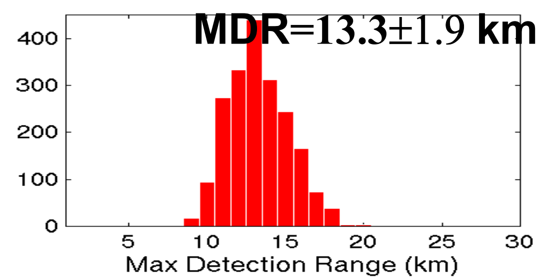
Incoherent TL



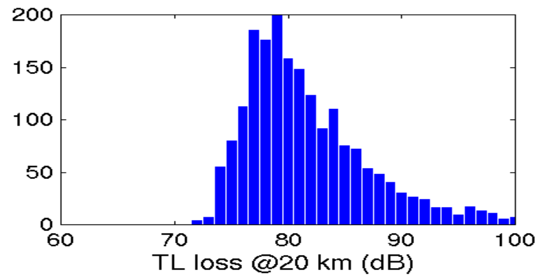


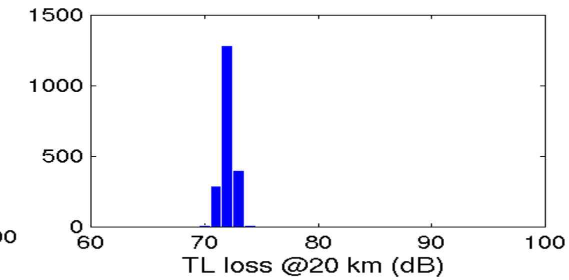
Maximum detection range using a 70-dB Figure of Merit.





TL@20 km
The shape is non-Gaussian.
We cannot just interpolate
TL at sound-speed endpoints.

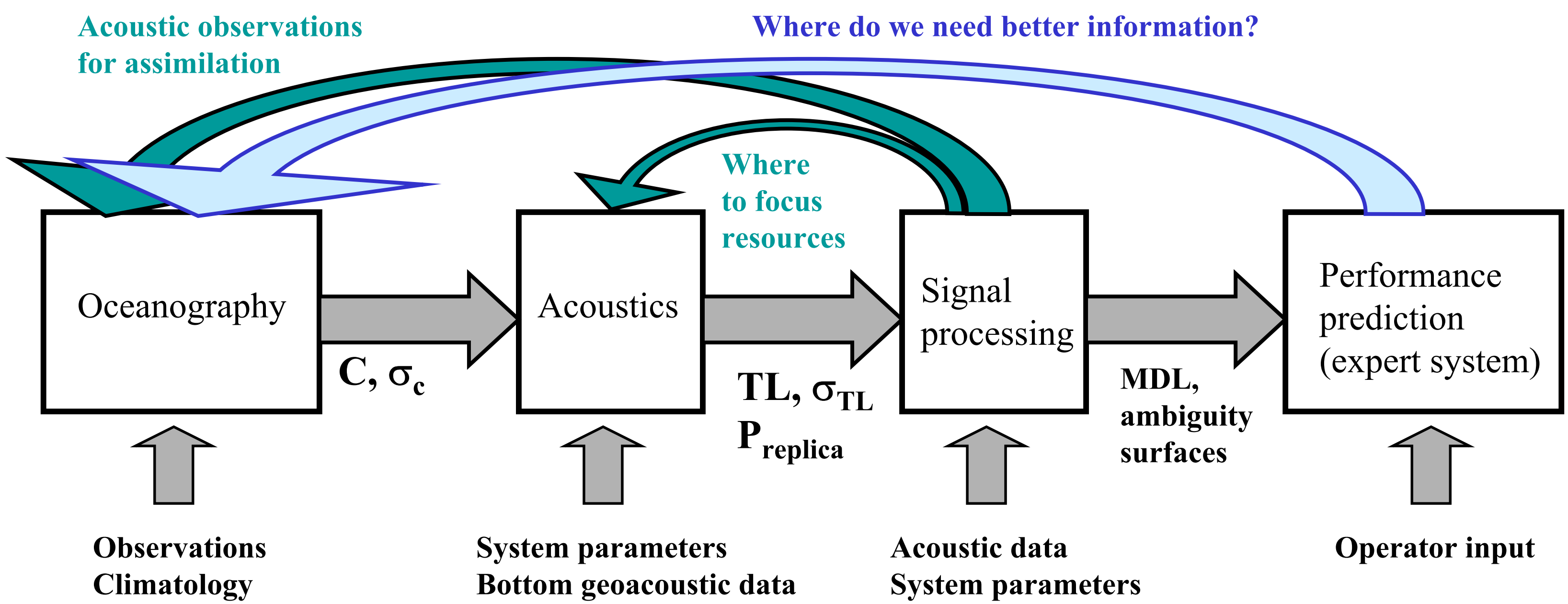




Conclusions

- Oceanography and Bathymetry significantly impact Performance Prediction.
  Other factors: Noise Structure, System Parameters
- Single Profiles lead to poor predictors in complex regions.
- Predictions enhanced over single profiles by including oceanographic features and (reduced number of) profiles.
- Uncertainty in sonar performance prediction can be propagated through a performance prediction model.

Flow of uncertainty information



Each stage feeds back information based on its sensitivities about which uncertainties hurt it the most.

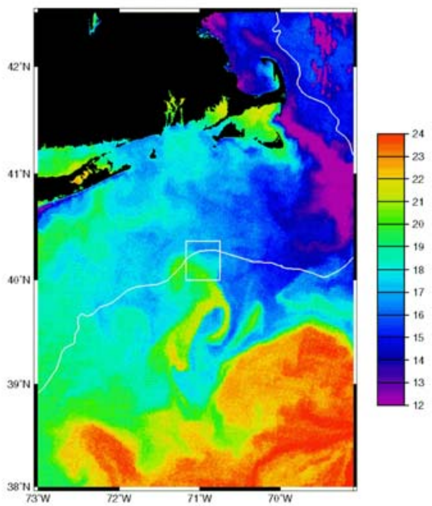
Physical Oceanography - goals

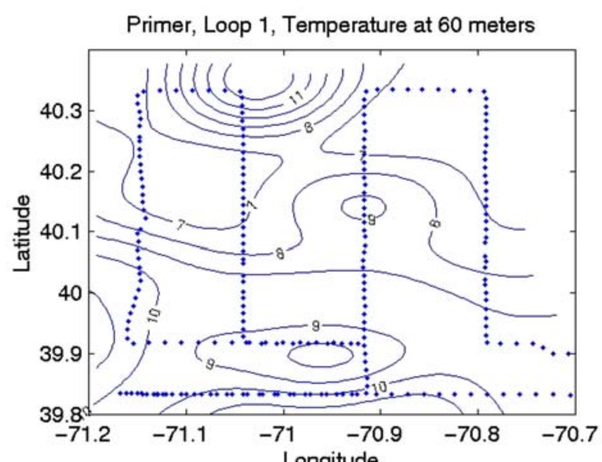
- Produce a hierarchy of 3-D sound speed fields and associated uncertainty for the acoustic modelers.
- The products will tie the data together with increasingly detailed dynamic constraints from ROMS/TOMS.
- All methods are least-squares, and the uncertainty will be communicated in terms of (factored) covariances:

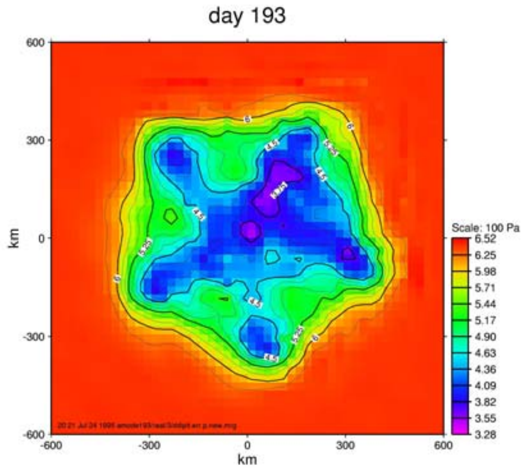
$$d = G \cdot m + r$$

$$\hat{m} = C_m G^T \left[G C_m G^T + C_r \right]^{-1} \cdot d$$

$$\widehat{C} = C_m - C_m G^T \left[G C_m G^T + C_r \right]^{-1} G C_m$$







Kuperman et al, June 2001

Physical Oceanography - goals

- **Products:**
  - *Climatology (Historical Mean, Covariances)*
  - *Objective Mapping (Gauss Markov interpolation)*
  - *Green's function assimilation*
  - *Adjoint assimilation (not yet operational)*

- **Intended to complement Harvard efforts:**
  - *Model comparisons: ROMS,HOPE,..*
  - *Estimate comparisons: Hard constraints vs Soft*

Physical oceanography - technical issues

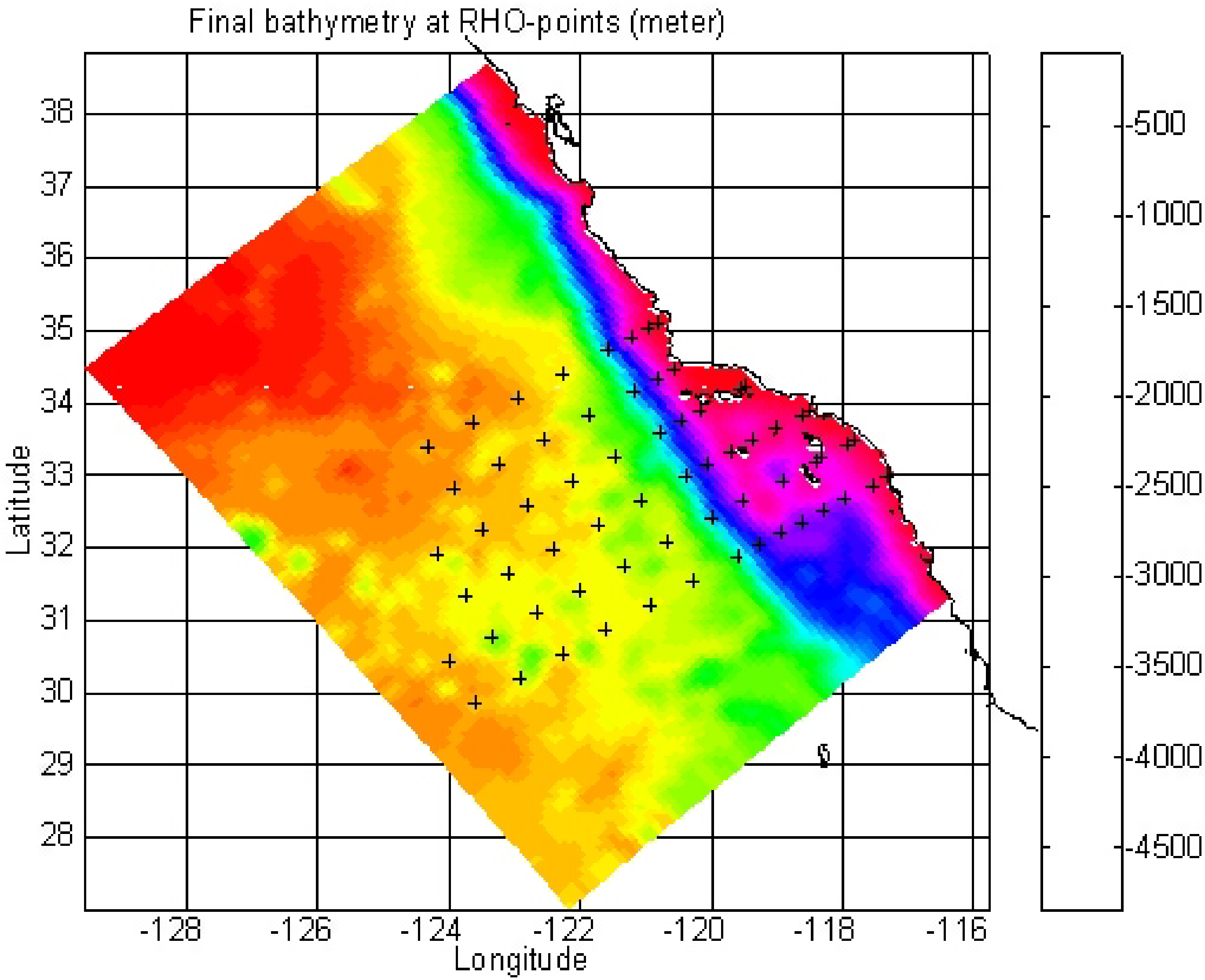
- **Interfaces from oceanographic to acoustic models**
  - *Offline first, then online*
  - *Interpolation: resolution, smoothness and bias*
- **Efficient representation of the uncertainty for both assimilation and acoustic modeling**
- **Green's functions for basis functions from factorization of the uncertainty covariance matrices**
- **Compatibility of uncertainty representations (physical vs acoustic)**
- **Predictability/linearity horizons for time-dependent syntheses**
- **Adjoint as complementary approach - addresses poor convergence**
- **Compatibility of 3-D initializations between models**
- **Comparability of model evolution (gives practical estimate of model error)**

Physical oceanography - issues for this meeting

Looking for cooperation - want to avoid unwanted overlaps:

- **Data**
  - *Quality control*
  - *Mapping*
  - *Model initialization*
- **Topography**

Model bathymetry and data location



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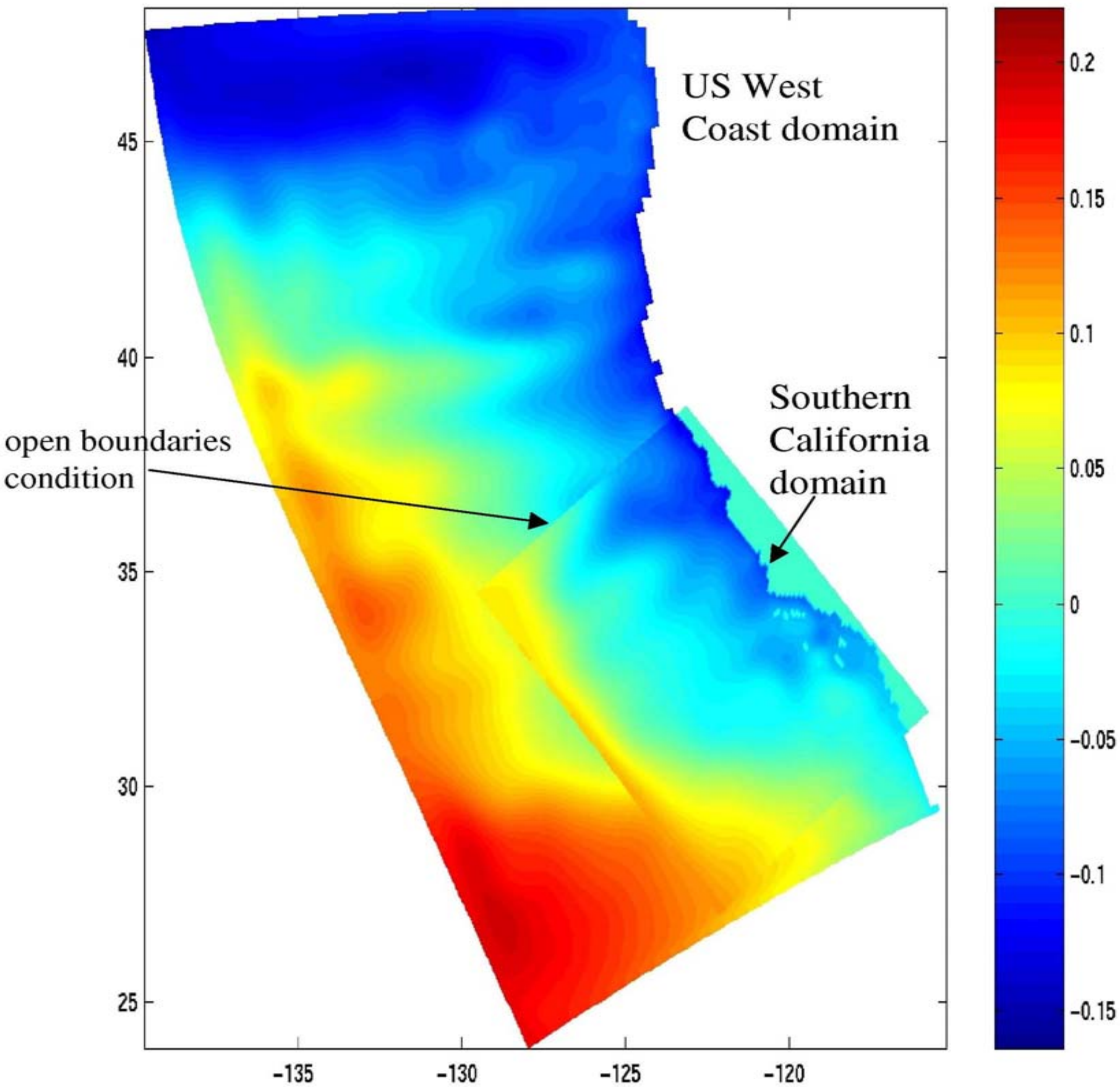
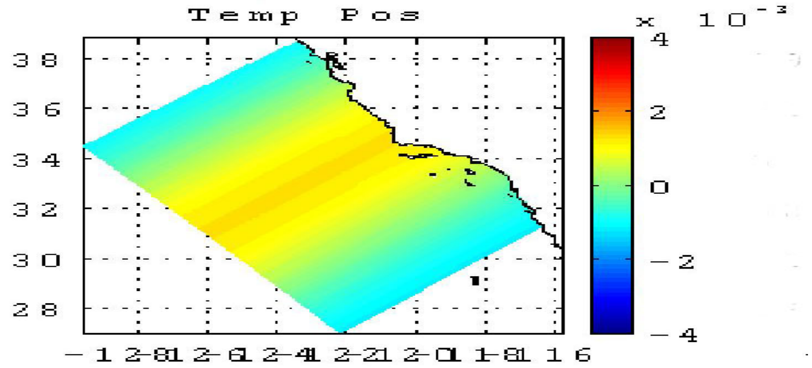
Modeled free-surface climatology

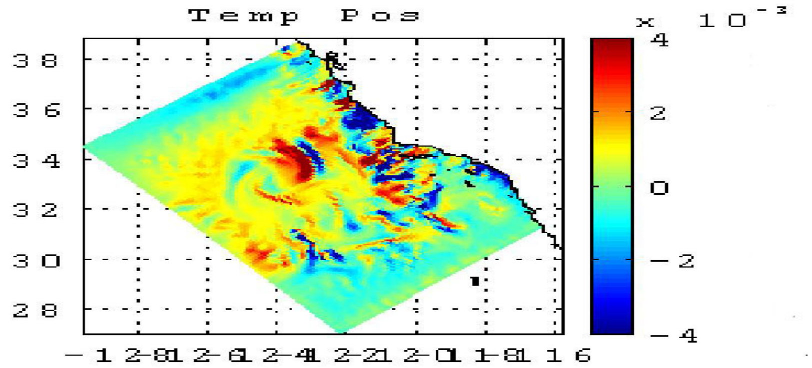


Green’s function example

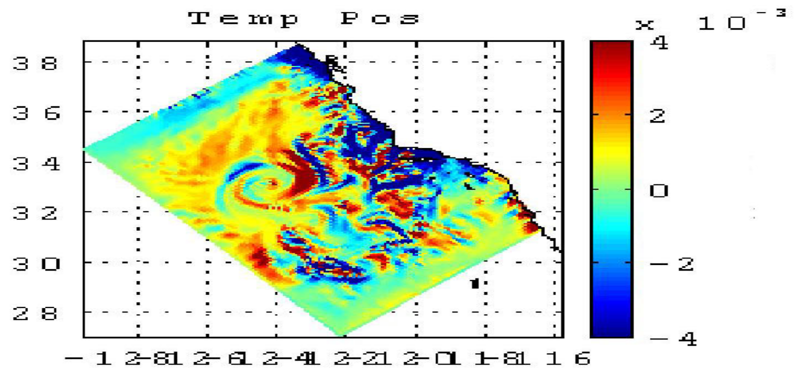
Initial perturbation



5 days later



9 days later



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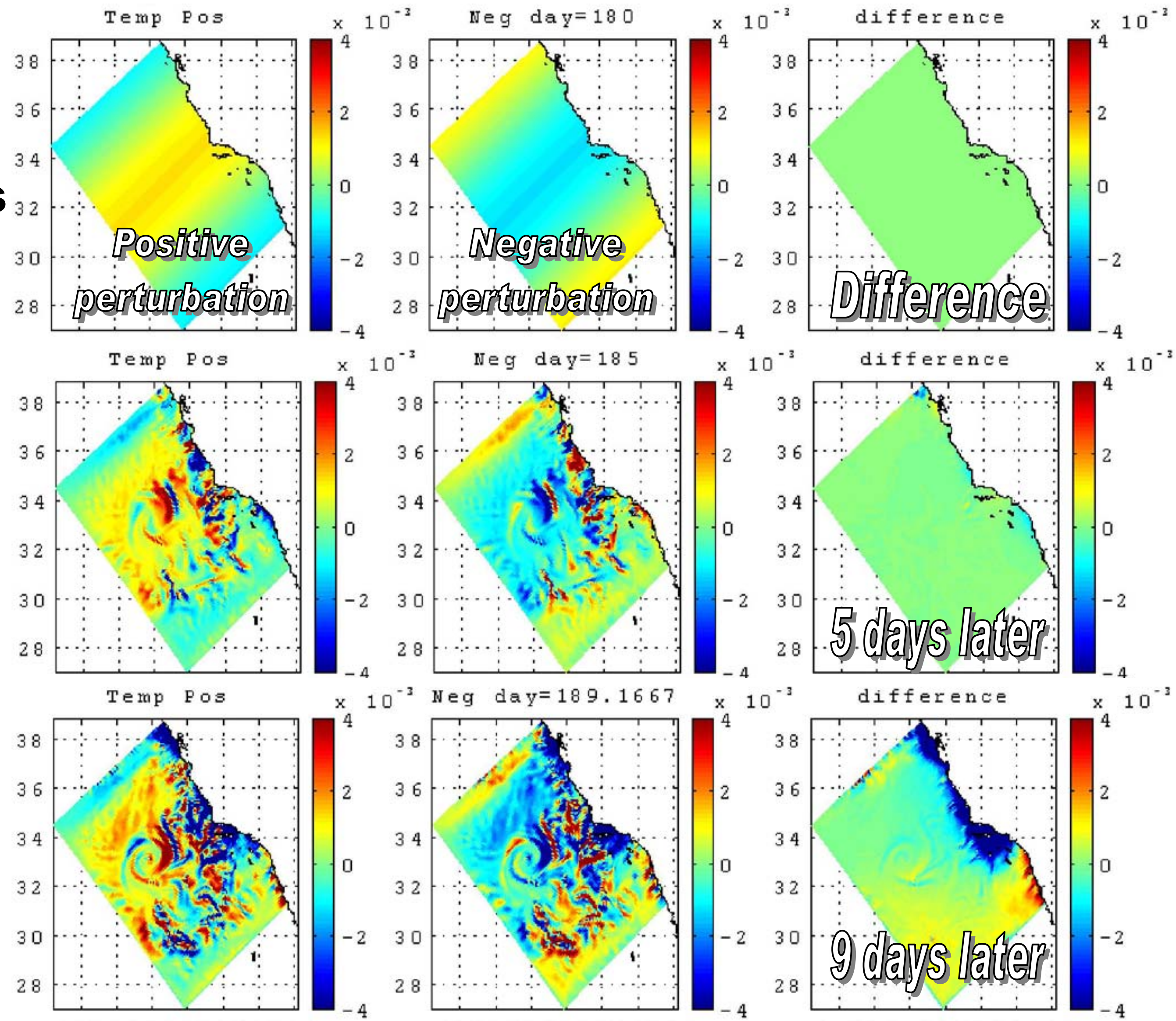
Spatial distribution of non-linearities

Assess linearity by comparing two perturbations of opposite sign.

At 5 days, system is still linear.

At 9 days, system is no longer linear.



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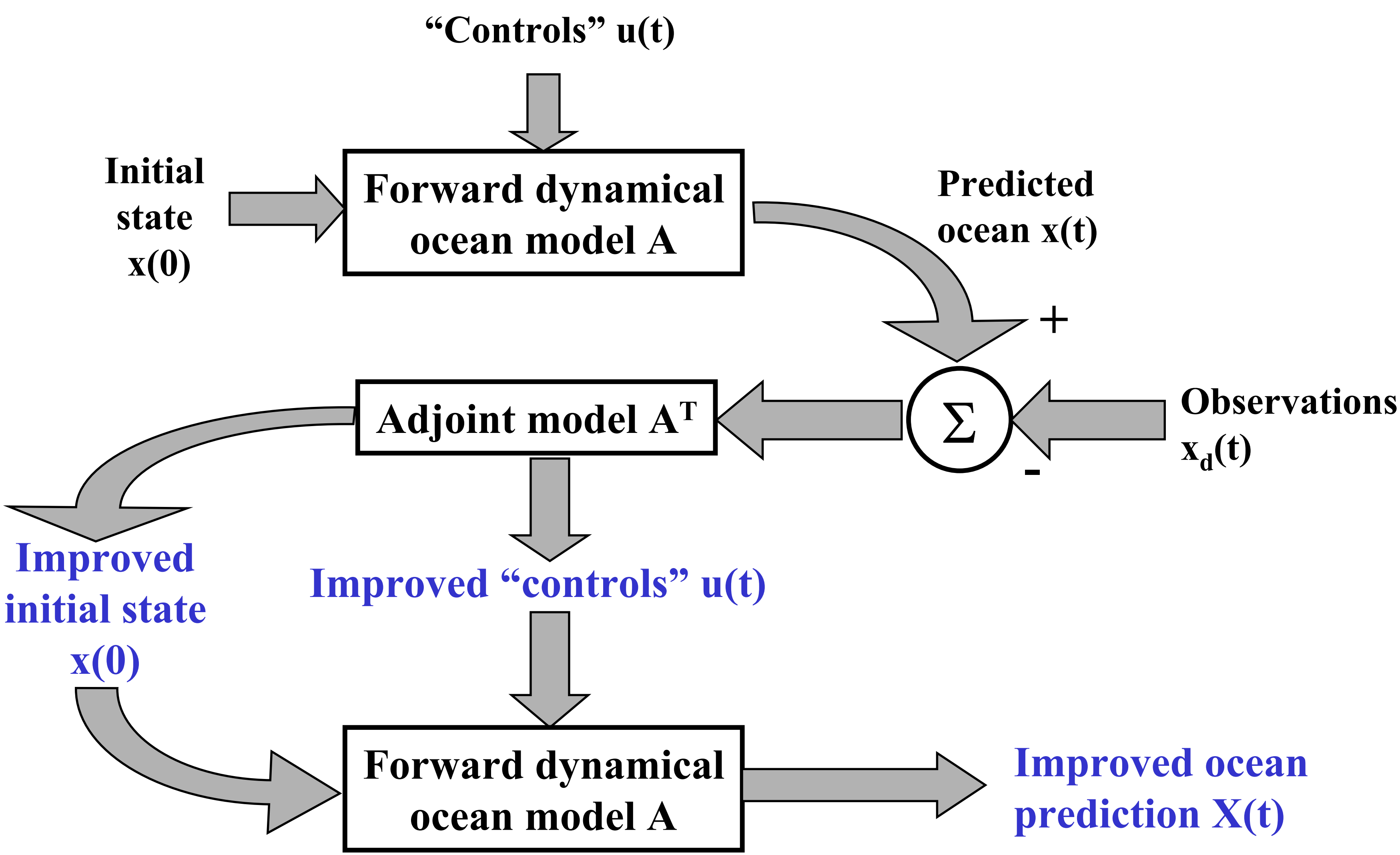
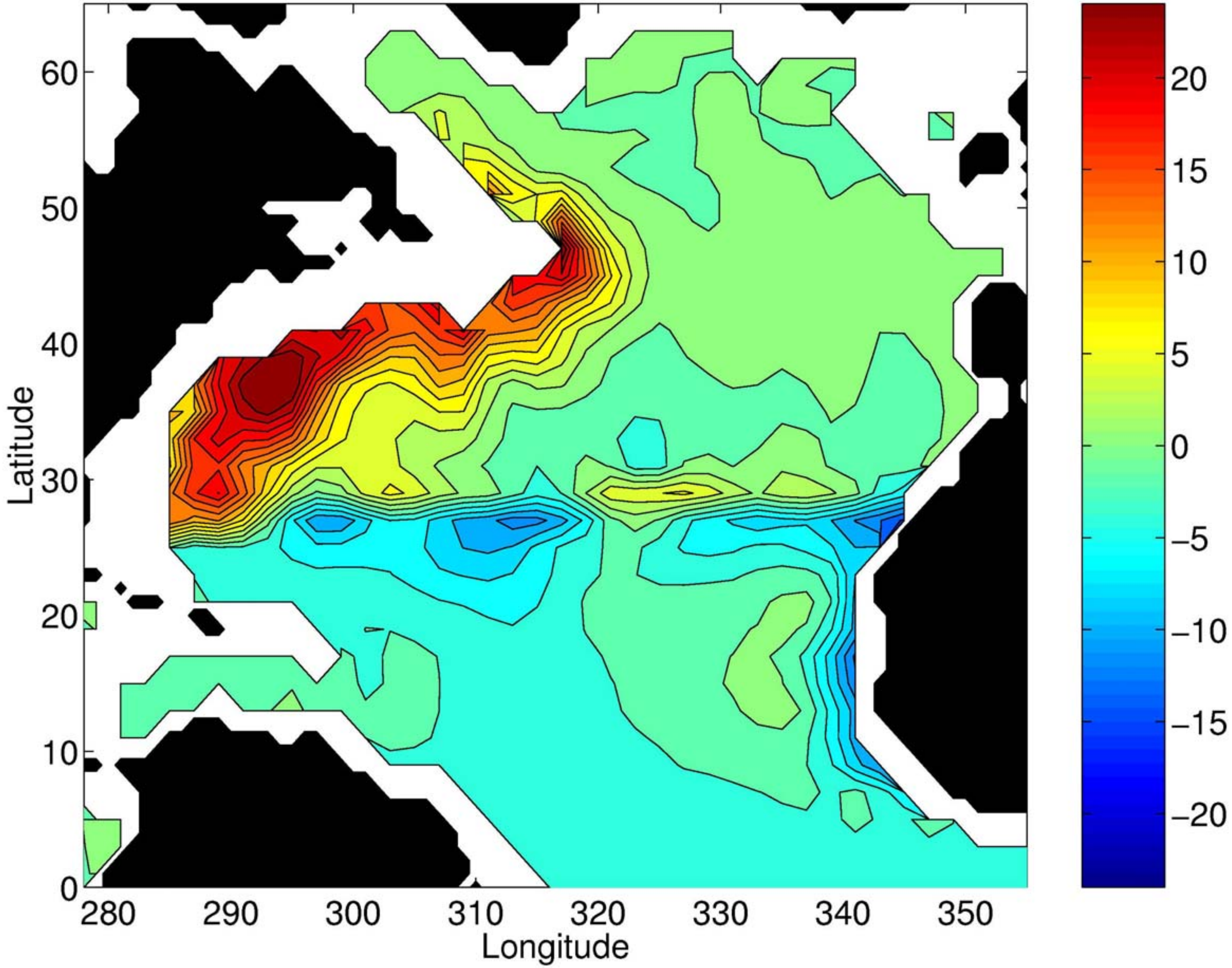
Adjoint



"Controls" u(t)
Initial state x(0)
Forward dynamical ocean model A
Predicted ocean x(t)
+
Σ
-
Observations $x_d(t)$
Adjoint model A^T
Improved initial state x(0)
Improved "controls" u(t)
Forward dynamical ocean model A
Improved ocean prediction X(t)

29N Heat transport salinity sensitivity (1160m) [TW/psu]



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Internal Wave Ocean Variability

- **Oceanographic Model**
  - *Input:*
    - Ocean model: Range/Time dependent CTD-Data
    - Quantities: N(r,t), dc/dz(r,t), deltac(r,c)
  - *Two Internal Wave models*
    - Modified GM (Yang, Colosi and Brown)
    - Solitary Waves
  - *Sound Speed Variability*
    - $c(r,t) = c_0(r,t) + dc_{GM}(r,t) + dc_{Soliton}(r,t)$
- **Acoustic Effects of IW variability**
  - *TL (Broadband PE Modeling)*
    - Spatial Dependence of TL
    - Frequency Dependence
  - *System level effects*
    - TL Variability
    - Array Gain (Signal Degradation)
    - Noise Gain

Acoustics

Objectives

I. Suite of *models for* rapidly producing TL or pressure field and their *uncertainty* (Monte Carlo)

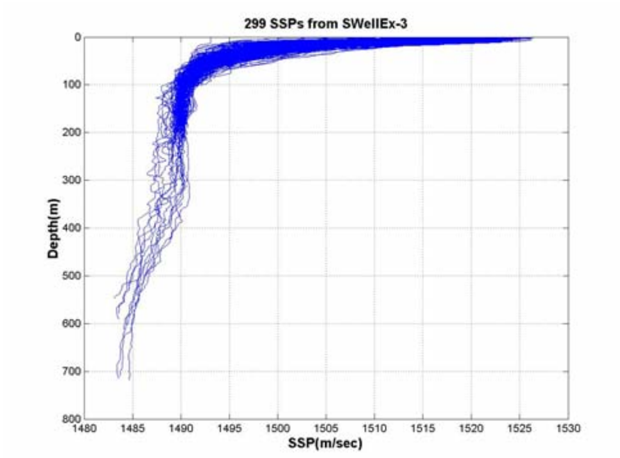
II. *Reducing uncertainty* by exploiting acoustic observables and feeding back to assimilation system

Approach: ‘environmental endpoints’ for

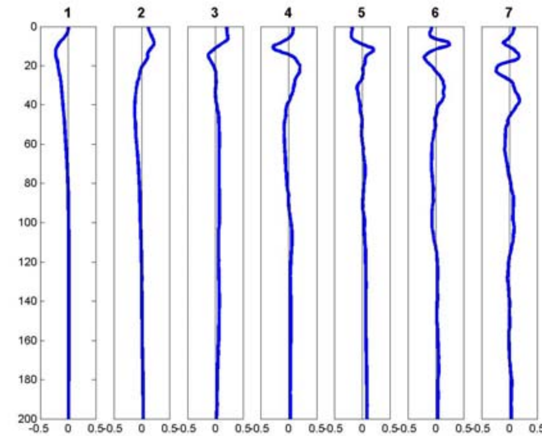
- Modes (KRAKEN, KRAKEN3D/Wide-area Rapid Acoustic Prediction)
- Rays/Beams (BELLHOP)
- Parabolic equation (RAM)
- Wavenumber integration (SCOOTER)

Environmental Basis Functions (EOFs)

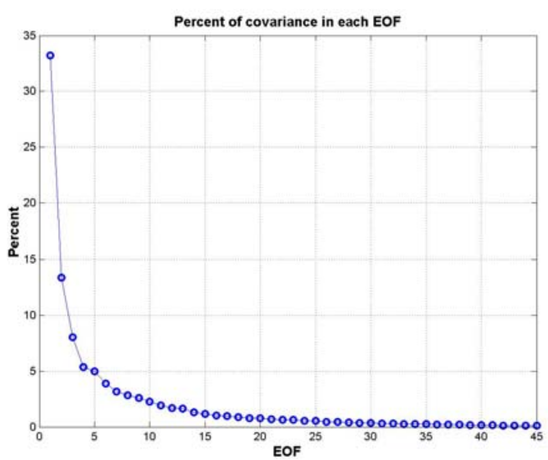
An ensemble of SSPs



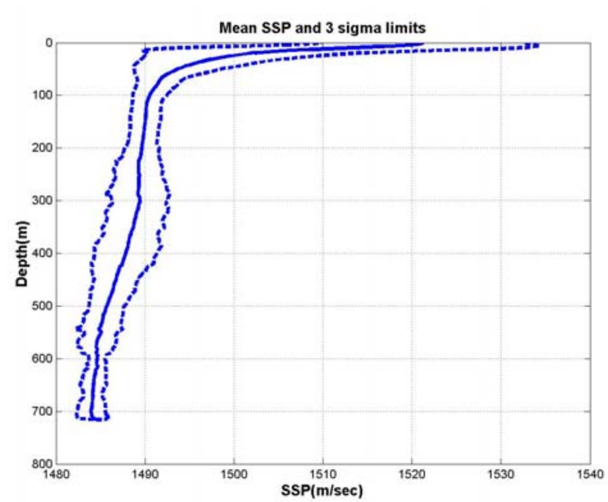
is decomposed into a set of basis functions



which progressively capture the variation



and are used to generate SSP realizations



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Environmental endpoints: Modal formulation

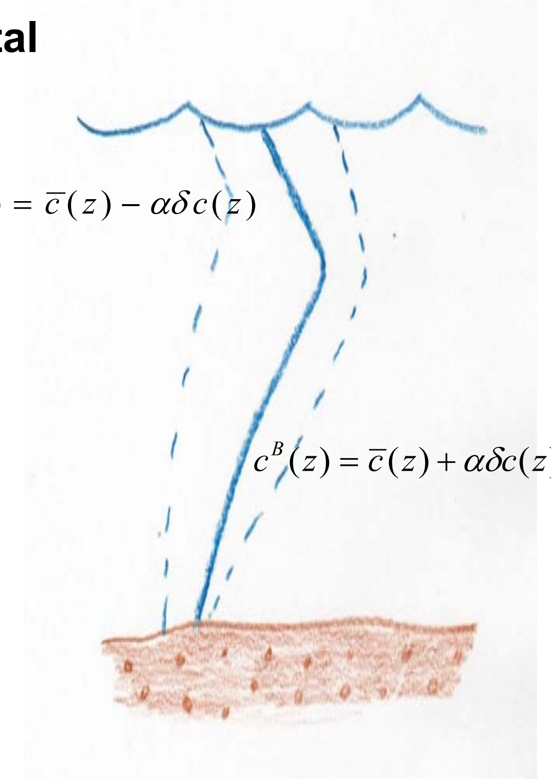
- **Characterize ocean uncertainty as a mean environmental basis functions:**

$$c^{\alpha}(z) = \overline{c}(z) + \alpha\delta c(z)$$

- **Pressure can be written**

$$p^{\alpha} = \overline{p} + \alpha\delta p$$

but p is not very linear



- **Modes:** $$p(r,z) = \sum_j Z_j(z_s) Z_j(z) \frac{e^{ik_j r}}{\sqrt{k_j r}}$$

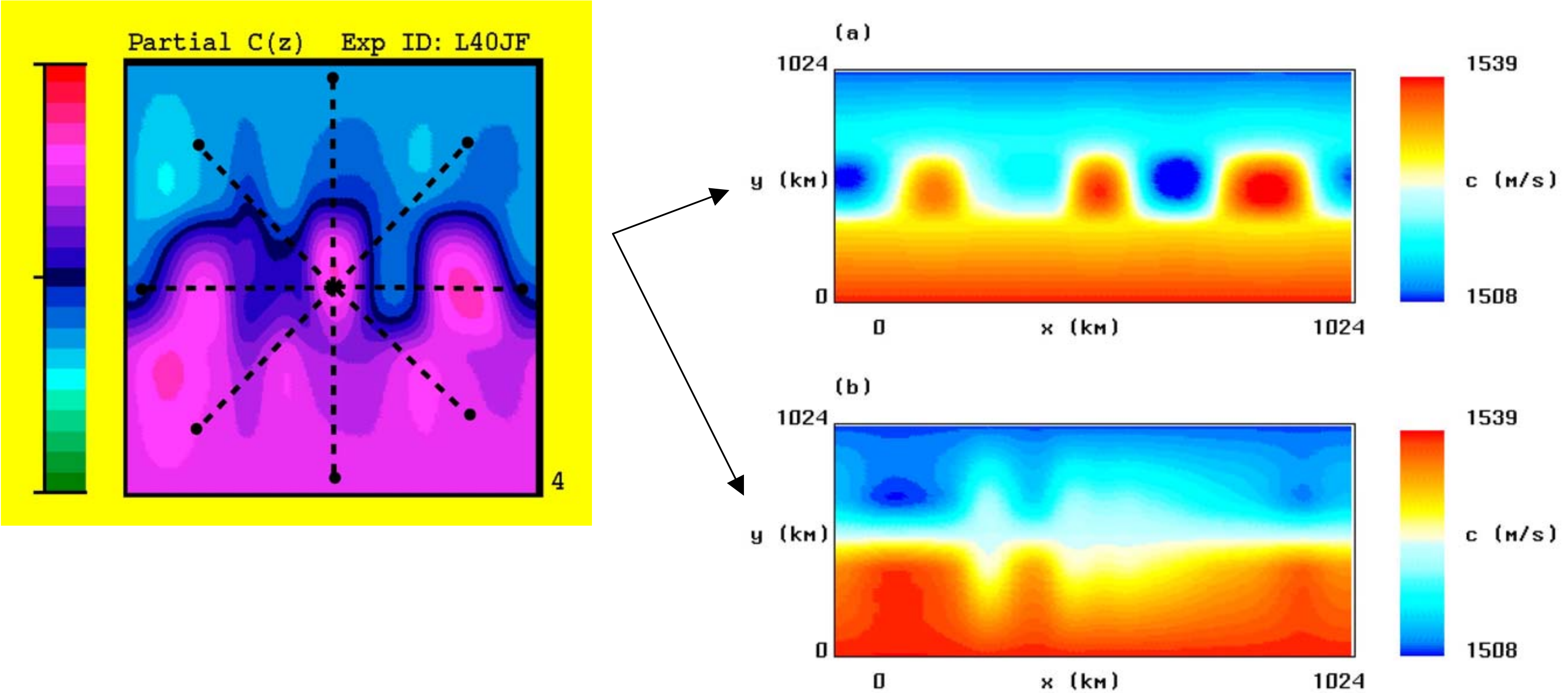
- **Wavenumbers *are* linear:** $k^{\alpha} = \overline{k} + \alpha\delta k$

- **Range-dependent and 3D extension is straightforward (in the adiabatic approximation)**

3D Generalization: Construct N, volumetric basis functions

Gulf Stream scenario

Environmental basis functions
(2 of N)



Environmental Endpoints: Ray/beam tracing formulation

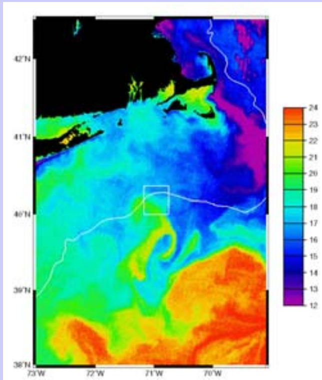
Frequency domain: $$p(r,z,\omega)=\sum_j A_j e^{i\omega(t-t_j)}$$

Time domain: $$p(r,z,t)=\sum_j A_j^r s(t-t_j)+A_j^i \hat{s}(t-t_j)$$

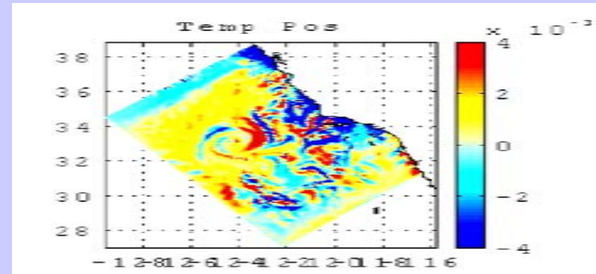
Eigenray amplitudes, A_j, and travel times, t_j, are linearized, e.g.:
$t_j = s\, t_j^A + (1\text{-}s)\, t_j^B$

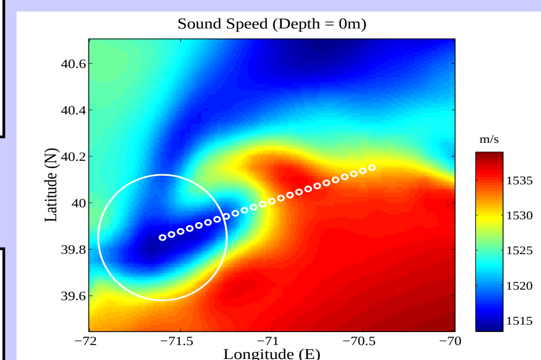
Closing the loop: Adjoints

ROMS initialization



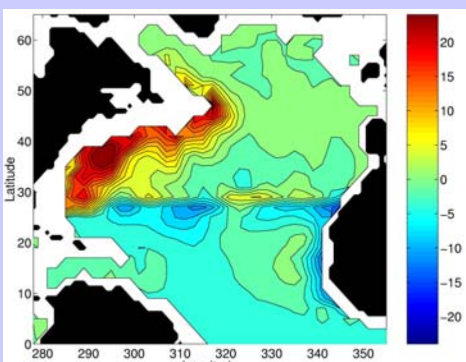
ROMS nowcast





Acoustic observables

Adjoint back-propagation



Correct initial conditions

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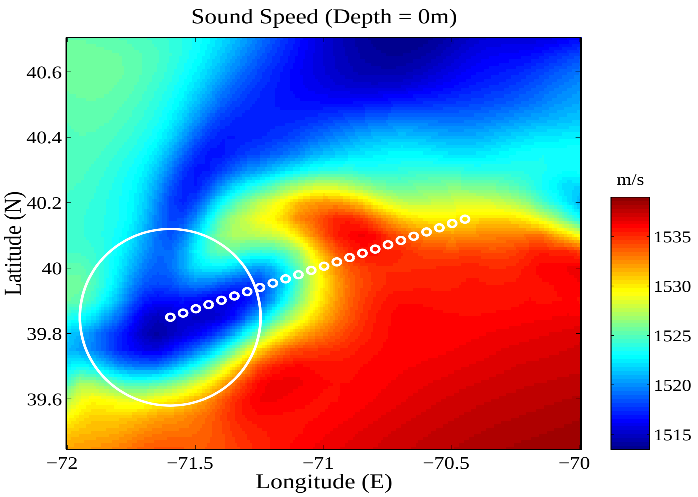
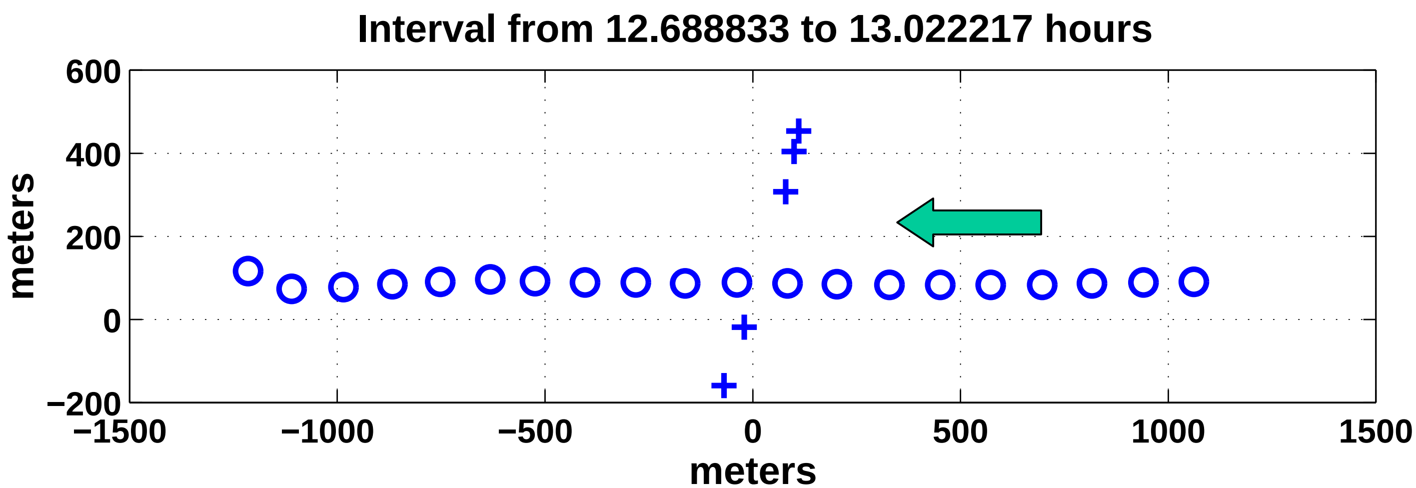
Proposed 'through the sensor' observables (that are also linear)

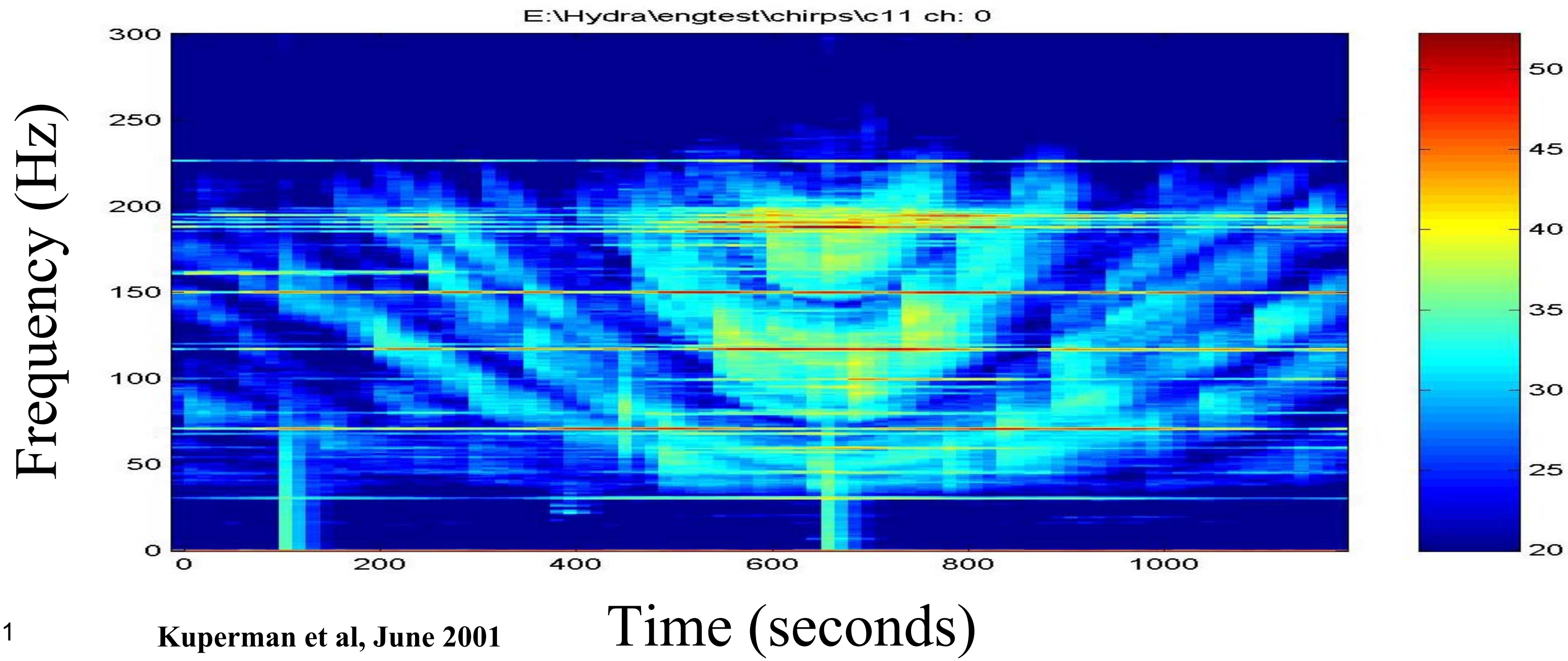
- **1/3-octave averaged intensity** (traversing ship maps out the environment through its intensity pattern)
- **Auto-correlation/cross-correlation** of channel impulse response
- **Beta** (slopes of the bathtub patterns)



All of the above are observable on towed-arrays as surface ships cross the scene

Example: Hydra sea test





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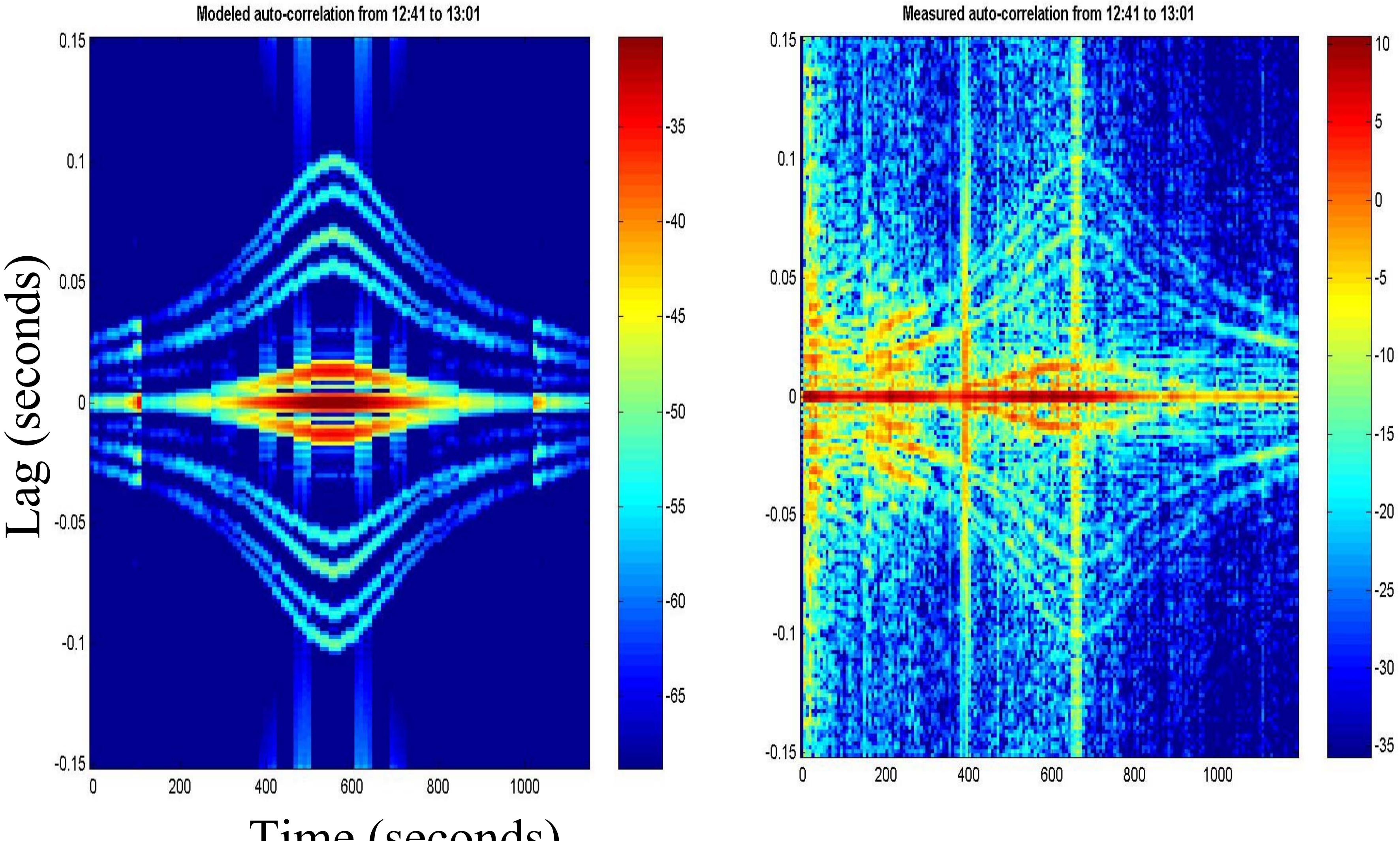
Modeled vs. measured auto-correlation waveforms



Limits to Sonar Performance in an Uncertain Ocean

Objective:

- To efficiently incorporate statistical characterizations of oceanographic uncertainty into detection performance bounds that are at least 10 dB more accurate than the conventional SONAR equation.

Summary:

- The classic SONAR equation, derived assuming a known ocean, can give erroneous performance predictions when the propagation environment is mismatched.
- Earliest work to incorporate environmental uncertainty into sonar prediction, performed by Bangs and Schultheiss (1971) and Cox (1973), was limited to Gaussian acoustic wavefront models without direct coupling to oceanographic uncertainty.
- Cramer-Rao-type bounds for source localization in an uncertain ocean studied by Baggeroer et.al. (1988), Li and Schultheiss (1993), and Narasimhan and Krolik (1995) are only tight at high SNR.
- Richardson and Nolte (1991) considered the source localization problem in an uncertain ocean using a Bayesian formulation which is readily adaptable to the prediction of detection performance.
- In this project, Nolte will examine bounds on optimal detection performance by Monte Carlo evaluation of likelihood ratio tests over ensembles of realistically simulated ocean realizations.
- In order to facilitate in situ performance prediction, Krolik will develop reduced-dimension representations of random oceanographic state variables which will facilitate efficient computation of sonar performance in uncertain ocean environments.

Performance Prediction Beyond the SONAR Equation

- Sonar detection formulated as a hypothesis testing problem where the likelihood ratio test (LRT) test, $\lambda(x,\theta)$, depends on array data x and hypothesized target location, θ
- Detection performance characterized by receiver operating characteristic (ROC) which requires estimation of

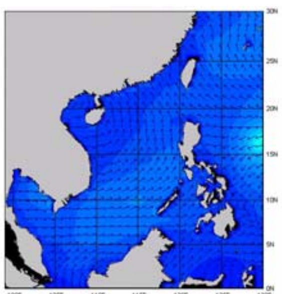
$$P_d(\theta) = \Pr(\lambda > \gamma \mid \theta, H_1) \text{ vs. } P_{FA} = \Pr(\lambda > \gamma \mid H_0).$$

- Performance in an uncertain ocean characterized by

$$\hat{P}_d(\theta) = \sum_{m=1}^{M} \Pr(\lambda > \gamma \mid \theta, \mathbf{g}_m, H_1)$$

where the $\boldsymbol{g}_k$ are Monte Carlo realizations of the ocean parameters.

- Classic SONAR equation uses a single ocean realization (M=1). Direct approach in uncertain environment requires large M to ensure critical ocean features represented.



Generate M Ocean Realizations

Detection Probability vs. Bearing/Range/Depth

Grid Theater of Operation

Predict Acoustic Wavefronts at Array for N Target Locations

Monte Carlo CDF of Detection Statistic

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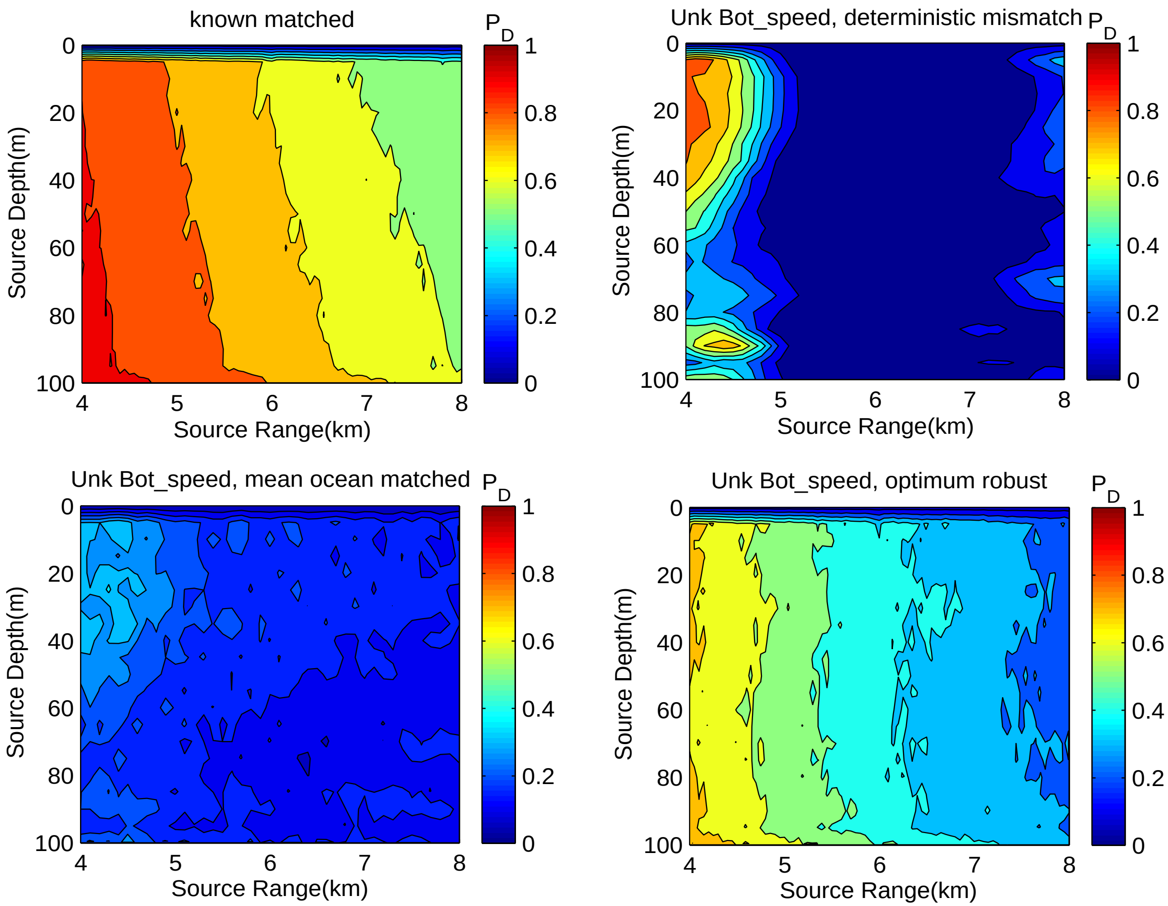
Example ROC Performance Surface

Known ocean, matched
Uncertain bottom speed, mean ocean matched

Uncertain bottom speed, deterministic mismatch
Uncertain bottom speed, optimum robust



Probability of Detection, P_d, for Probability of False Alarm, $P_{fa} = .05$, in an Uncertain Ocean as a function of Range and Depth

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Reduced-Dimension Representation of Ocean Uncertainty

- To reduce the number, *M,* of ocean realizations needed "on-line", determine a reduced dimension basis "off-line" which captures salient sound-speed profile characteristics.
- For example, suppose $Z(\mathbf{g}) = [E(\lambda\,|\theta_1, \mathbf{g}, H_1), \ldots, E(\lambda\,|\theta_s, \mathbf{g}, H_1)]$ determines probability of detection for length N ocean state vector, g, over a fine grid of hypothesized source positions.
- Reduced-dimension representation for the environment involves finding $L<N$ basis vectors for ocean uncertainty, $\mathbf{U=[u_1,\vdots\ldots\vdots,u_L]}$, which minimizes:

$$J = E_g\,(\;|z(UU^{+}g) - z(g)|^2\;)$$

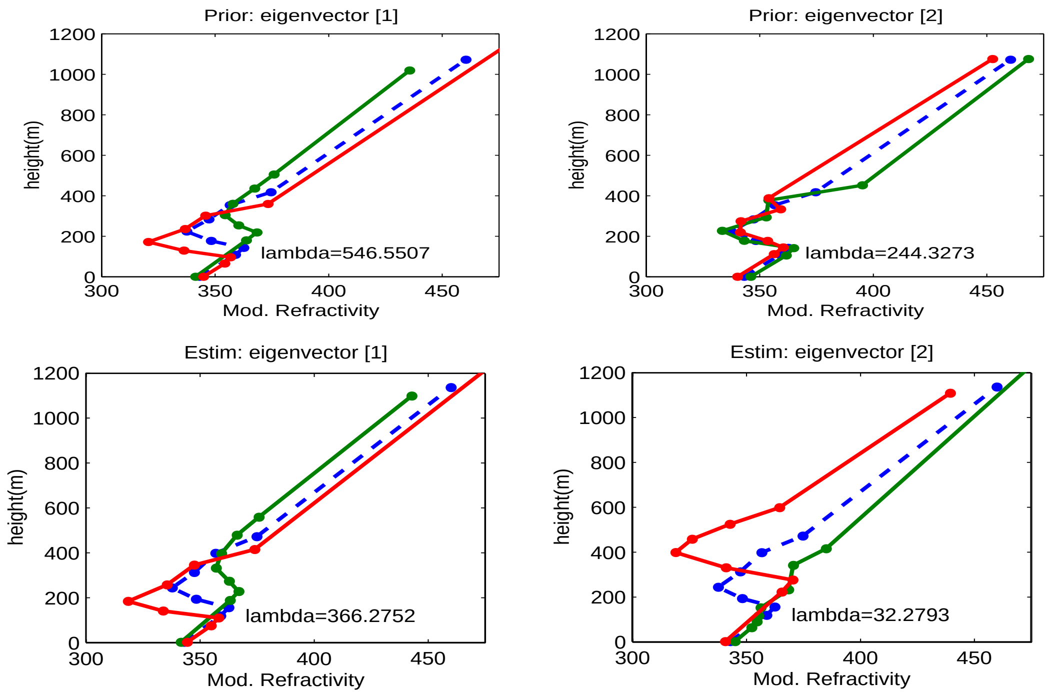
- For illustrative purposes only, if **z=H(g),** then this problem is equivalent to finding **U** that minimizes:

$$J = H\,(\mathrm{I} - \mathbf{UU}^{+})\,Cov(\mathbf{g})\,(\mathrm{I} - \mathbf{UU}^{+})\,H^{+}.$$

- Optimum basis involves trade-off between being in the span of dominant eigenvectors of $Cov(\mathbf{g})$ (which would be Karhunen-Loeve basis) versus the span of H (sensitivity to transformation from ocean state to sonar detection statistic).

Example of Efficient Basis Selection in Refractivity Estimation

- In recent work, we have worked analogous problem of finding best bases for microwave refractivity estimation using low-angle radar clutter backscattered from the sea surface.
- Dominant refractivity eigenvectors for KL (upper) and generalized KL bases (lower).



- Note that second basis vector for GKLT much more efficiently captures profile characteristics which affect propagation in a surface-based duct